

## MRE-based Bayesian inversion of seismic and EM data for identification of reservoir parameters

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### SUMMARY

A stochastic joint inversion approach for estimating reservoir fluid saturations and porosity is proposed. The approach couples seismic amplitude versus angle (AVA) and marine controlled source electromagnetic (CSEM) forward models into a Bayesian formalism, which allows for integration between complementary information. To obtain minimally subjective prior probabilities required for the Bayesian approach, the principle of Minimum Relative Entropy (MRE) is employed. Instead of single-valued estimate provided by deterministic methods, the approach gives a probability distribution for any unknown parameter of interest, such as reservoir fluid saturations or porosity at different locations. The distributions means, modes, and confidence intervals can be calculated, providing a more complete understanding of the uncertainty in the parameter estimates. The approach is tested using two case studies: one is a synthetic case, and the other uses data from the North Sea Troll field. Results show that joint inversion using seismic and EM data gives better estimates of reservoir parameters than estimates from either geophysical data set used in isolation.

### INTRODUCTION

To estimate reservoir fluid saturations and porosity is the goal of many geophysical surveys in hydrocarbon exploration and production. Changes in pore pressure and water saturation can be predicted when only oil and water exist. However, the presence of gas may make the estimation problem complicated and ill-posed. This is primarily due to insensitivity of acoustic ( $V_p$ ) and shear ( $V_s$ ) wave velocities to gas saturation. According to Gassmann's equations, a gas sand with one percent gas saturation can have the same  $V_p/V_s$  as a commercial accumulation of gas (Castagna, 1993). Previous studies on the inversion of seismic AVA data to predict seismic parameters (Plessix et al., 2000; Buland and More, 2003) has concluded that current seismic technology cannot reliably be used to distinguish economic from non-economic gas accumulations, resulting in significant exploration losses. Regardless of this inability, seismic technology can provide two critical pieces of information needed for the ultimate estimation of gas saturation: the first the physical location of the reservoir unit, to within a few percent of true values, and the second is the porosity of the reservoir unit. In contrast, electrical resistivity of reservoir rocks is highly sensitive to gas saturation, which is known as Archie's Law (Archie, 1942). The dependence of the bulk resistivity is useful for discriminating economic from non-economic gas. The means of providing estimates for bulk

resistivity have recently become available through the use of CSEM sounding systems. A combination of the two types of data has the potential to improve reservoir parameter estimates in a joint inversion, since they provide different and complementary images of the geology. This is not a new idea, and works along this line were reported (e.g., Tseng and Lee, 2001 and Hoversten et al., 2003), but many challenges need to be addressed before such integration becomes suitable for common applications: (a) Different types of data, as well as data originating from different sources, are characterized by different error levels which are not always known prior to the inversion. Thus, methods are needed for modeling such errors with minimum bias; (b) Deterministic inversion is often an ill-posed mathematical problem due to non-uniqueness and instability. This in turn suggests that inversion formulated in a stochastic framework (Rubin, 2003) may be more robust than traditional deterministic approaches, but an effort is needed to identify suitable stochastic formulations and to address specific issues such as computing efficiency; (c) Prior information is available, in many cases, to constrain the inversion. Such data may be available, for example, from geologically-similar formations, in the form of imprecise information such as statistical moments. Questions then arise as to what should be the relative weight such prior information should be assigned compared to information available from in-situ measurements, and what would be a rational approach for formulating such prior information within the stochastic framework.

### METHODOLOGY

Seismic data used for this study are pre-stacked angle gathers that have been normal moveout corrected and processed to remove multiples. After appropriate seismic processing (including amplitude recovery) we can assume the seismic attenuations in the earth above the target interval (the overburden) have been accounted for and so can be neglected in the seismic modeling. But overburden  $V_p$ ,  $V_s$  and  $\rho$  above the target are included in the parameters to be inverted because we choose a time window of the seismic AVA data in seismic inversion and it is possible that the window does not match exactly the target (reservoir) zone, especially when the available velocity model that we used for time to depth conversions is not perfect. Marine CSEM data used in this study are the amplitudes and phases of the recorded electrical field from many receivers located on the seafloor. These data measure the response to the electromagnetic field induced in the domain which encompasses the seawater, the overburden above the reservoir, the reservoir itself, and the sediments below the reservoir.

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The seismic AVA and the EM calculations require different modeling domains, thus the unknowns to be estimated from the seismic data inversion include  $S_w$ ,  $S_g$ , and  $\phi$  in target zone, as well as  $V_p$ ,  $V_s$  and density  $\rho$  in the layers below and above the target zone. The layer thicknesses can also be considered as unknowns. The unknowns in EM data inversion include  $S_w$ ,  $S_g$ , and  $\phi$  in target zone, as well as  $\sigma_{conductivity}$  and  $\sigma_{overburden}$ .

We represent the vector of target variables stated above together by  $\mathbf{m}$ . To account for parameter uncertainty,  $\mathbf{m}$  is viewed as a realization of a random vector  $\mathbf{M}$ , which is characterized by a  $p$ -variate probability distribution function (pdf)  $f_M(\mathbf{m})$ , where  $p$  is the total number of parameters in  $\mathbf{M}$ . The first  $k$  moments of  $\mathbf{m}$  can be calculated as  $\langle \mathbf{m}^k | \mathbf{I} \rangle = \int \mathbf{m}^k f_M(\mathbf{m}) d^p \mathbf{m}$ , which is the integration over the entire vector space of  $\mathbf{m}$ , from which we get the estimation (the first moments), as well as the predictive intervals of  $\mathbf{M}$ .

### Bayesian Theory

Our approach is based on Bayes' Theorem (cf., Rubin, 2003, Chapter 13):

$$f_M(\mathbf{m}) \equiv f_{M|D,I}(\mathbf{m}|\mathbf{d}^*, \mathbf{I}) = \frac{f_{D|M,I}(\mathbf{d}^*|\mathbf{m}, \mathbf{I}) f_{M|I}(\mathbf{m}|\mathbf{I})}{\int_{\mathbf{m}} f_{D|M,I}(\mathbf{d}^*|\mathbf{m}, \mathbf{I}) f_{M|I}(\mathbf{m}|\mathbf{I}) d^p \mathbf{m}}, \quad (1)$$

with boldface letters representing vectors. Capital letters denote random variables and lower-case letters denote their realizations. Here  $\mathbf{d}^*$  is a vector of measurements, which includes data obtained from both EM and seismic, and which we consider as a realization of a vector  $\mathbf{D}$ ;  $f_{M|I}(\mathbf{m}|\mathbf{I})$  is the prior pdf (probability density function) of  $\mathbf{m}$  given prior information  $\mathbf{I}$ .  $f_{D|M,I}(\mathbf{d}^*|\mathbf{m}, \mathbf{I})$  is the likelihood function, and  $f_{M|D,I}(\mathbf{m}|\mathbf{d}^*, \mathbf{I})$  is the posterior pdf. Simply stated, the likelihood function maps the prior into the posterior, based on the conditional pdf of the observations.

Our analysis consists of the following steps: 1) Modeling of the prior by use of the Minimum Relative Entropy (MRE), a systematic, analytic method to determine the prior pdf based on information such as bounds, means, or variances of the parameters, with minimum subjectivity; 2) Modeling  $\mathbf{d}^*$ : We assume  $\mathbf{d}^* = \mathbf{g}(\mathbf{m}) + \boldsymbol{\varepsilon}$ , where  $\mathbf{g}$  is a forward model, and  $\boldsymbol{\varepsilon}$  denotes measurement and possibly modeling errors. In our analysis  $\mathbf{g}$  can be either  $\mathbf{g}_1$ , where  $\mathbf{g}_1$  is a forward AVA model or  $\mathbf{g}_2$ , where  $\mathbf{g}_2$  is a forward EM model; 3) Modeling  $\boldsymbol{\varepsilon}$ : We assume that the errors are independent, of zero mean and unknown variance; 4) Prediction of the parameters using quasi Monte Carlo integration.

### Forward models

Forward geophysical modeling is used in the estimation of the likelihood function  $f_{D|M,I}(\mathbf{d}^*|\mathbf{m}, \mathbf{I})$ . Our analysis assumes that the underlying geological structure can be simplified as a layered 1D model. For the 1D seismic AVA model,  $\mathbf{g}_1$ , the Zoeppritz equation is used to calculate the angle-dependent reflectivity, which is convolved with an angle dependent wavelet to form the calculated seismic AVA responses

(Shuey, 1985). The modified Hashin-Shtrikman lower bounds (Hashin and Shtrikman, 1963) are used to calculate the effective moduli for porosities smaller than the critical value. This model is described by Dvorkin & Nur (1996) as applied to modeling velocity-pressure relations for North Sea Sand stones and its use in combined seismic and EM inversion is described by Hoversten et al. (2003). For the EM forward model  $\mathbf{g}_2$ , we employed an integral equation solution for the electric (E) field from an electric dipole source within a layered media (Ward and Hohmann, 1987). Archie's Law (Archie, 1942) is used to model electrical resistivity as a function of  $\phi$  and  $S_w$ . The fluid bulk moduli ( $K_{brine}$ ,  $K_{oil}$ ,  $K_{hcg}$ ) and densities ( $\rho_{brine}$ ,  $\rho_{oil}$ ,  $\rho_{hcg}$ ) of brine, oil and gas respectively are computed using relations from Batzle and Wang (1992).

### SYNTHETIC STUDIES

The performance of the model is illustrated using seismic and EM data inversion individually, as well as using joint inversion. We tested them on a simple reservoir model assuming known rock-properties. The synthetic seismic and EM dataset is generated from a 1D model with 1,000m of seawater over a conductive sedimentary sequence. The target horizon is 2,000m below the seafloor. The reservoir interval is comprised of five 30m-thick layers, two of which have high gas saturation. From the upper to bottom layer, the gas saturation values are 0.1, 0.95, 0.4, 0.9, 0.1, respectively. And the corresponding true porosity values are 0.15, 0.25, 0.15, 0.1, 0.05, respectively. The synthetic AVA is sampled 80 times at 2ms for five incident angles (0, 10, 20, 30, and 40 degrees). The synthetic EM data includes the amplitude and phase of the measured electric field at frequency 0.25Hz for 15 source-receiver offsets. Gaussian random noise was added starting with 10% noise for the first angle and increasing up to 30% at the far angle. Similarly, 10% Gaussian noise was added to the electric fields at the near offsets, increasing to 30% at the maximum offset. The prior bounds for porosity at each layer is assumed to be [0, 0.3] and for gas saturation, [0, 1]. This represents a uniform prior distribution of gas saturation and porosity based on MRE theory.

Results show that seismic inversion provides accurate estimation of porosity but poor estimates for gas saturation because the seismic AVA responses are insensitive to gas saturation changes. Joint inversion using seismic and EM data provides better estimates of gas saturation and porosity at all layers compared to individual seismic and EM inversion. Moreover, inversion using multiple-frequency EM data gives more accurate results than using single frequency EM data, which is reasonable as more information is included.

### TROLL FIELD STUDIES

In this section, we apply our MRE-based Bayesian approach to the Troll field site in North Sea, where 3D seismic and marine CSEM data were acquired over a portion of the Troll field in 2003. The 3D seismic data was pre-stack time migrated and sorted into common-midpoint gathers. NMO and residual NMO was applied along with multiple removal and filtering to a nominal zero-phase wavelet. The offsets were converted to angles by ray-tracing a layered model with velocity and density taken from a well nearby. Depth-time

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pairs were generated from the well to determine the time window for the seismic data such that the data covered the depth interval 100m above and below the reservoir zone. Marine EM data used in this study includes amplitudes and phases of the recorded electrical field from many receivers along a survey line located on the sea. Deterministic and also a Bayesian approach using Markov Chain Monte Carlo method have been tested and gave good reservoir parameter estimations using Troll filed data (Hoversten, et al., 2005; Chen, et al., 2004). Here individual and joint inversion using seismic and EM data are performed. Results show that joint inversion improves our estimates of both porosity and gas saturation as it gives predictions that are closer to well logs and gives narrower predictive intervals.

### CONCLUSIONS

We proposed here a MRE-Bayesian approach for joint seismic and EM inversion. Our preliminary results on synthetic data indicate that joint inversion based on seismic and EM data improves our capability to identify and confirm the locations of gas-rich layers. Seismic AVA responses can be used to identify the porosity very well. However, the responses are not sensitive to gas saturation changes, thus incorporation of EM data in the inversion is warranted, and is proven to be useful in improving our ability to predict gas saturation. The approach is also applied to the real data at Troll field in North Sea. Results show the benefits of combining EM data with seismic data. Compared to any individual inversion using either seismic or EM data, the joint inversion gives predictions that are closer to well logs and gives narrower predictive intervals, which means the ambiguity or uncertainty associated with the parameters is reduced.

The advantage of formulating this inverse problem in a stochastic framework manifests here in the statistics of the target parameters. Instead of the usual single-valued estimation which is provided by the deterministic approach, we get a probability distribution, which allows to compute mean, mode and confidence intervals, and is useful for a rational evaluation of uncertainty and its consequences.

We made several important assumptions in the study. We assume the actual earth can be represented by 1D layers model, which could be inappropriate for EM dataset. For seismic data, we assume the effects of multiples and waveform spreading can be neglected and we assume the rock physics model parameters developed from the well logs nearby is true for our study site, etc. Many of the assumptions presented here can be overcome by increasing the complexity of both the seismic and EM models, for example, by considering 1D elastic seismic calculation with all multiples, mode-conversions and waveform spreading, or by considering 2D or even 3D forward models.

### ACKNOWLEDGEMENTS

The work is funded by the Research Partnership to Secure Energy for America (RPSEA) and the Assistant Secretary for

Fossil Energy, National Petroleum Office of the U.S. Department of Energy, under contract DE-AC03-76SF00098. We are grateful to Statoil for supplying the CSEM data over Troll and to EMGS and Shell for their contributions of data and consultations. In particular, we thank Tage Rosten of Statoil, Jaap Mondt and Maren Kleemeyer of Shell and Rune Mittet of EMGS. In addition, we thank the Troll partners (Norsk Hydro, Statoil, Petoro, Norske Shell, Total, and ConocoPhillips) for permission to publish this work.

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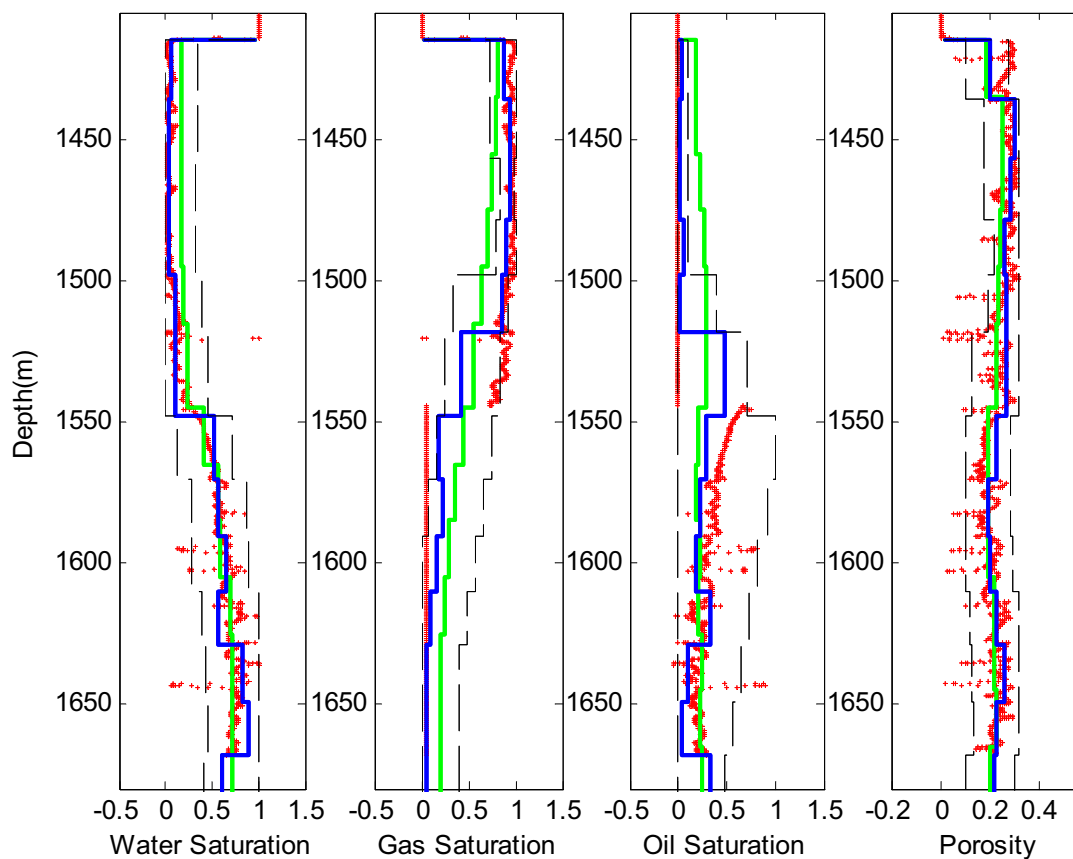


Figure 1. Joint inversion of water, gas, oil saturation using seismic and EM data. Red crosses represent well log values, green lines are the prior means, blue lines are the estimated posterior means, and black dashed lines represent 95% predictive intervals.

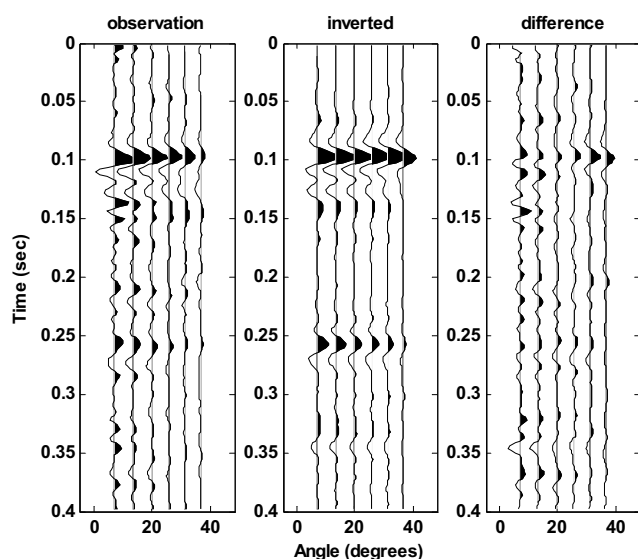


Figure 2. Observed seismic AVA gather (left panel), calculated AVA data from seismic only inversion (middle panel), and the difference between observed and calculated AVA data (right panel). Zero time corresponds to the top of the seismic inversion zone 100m above the reservoir. The top and base of the reservoir are at 0.1 and 0.37 seconds.

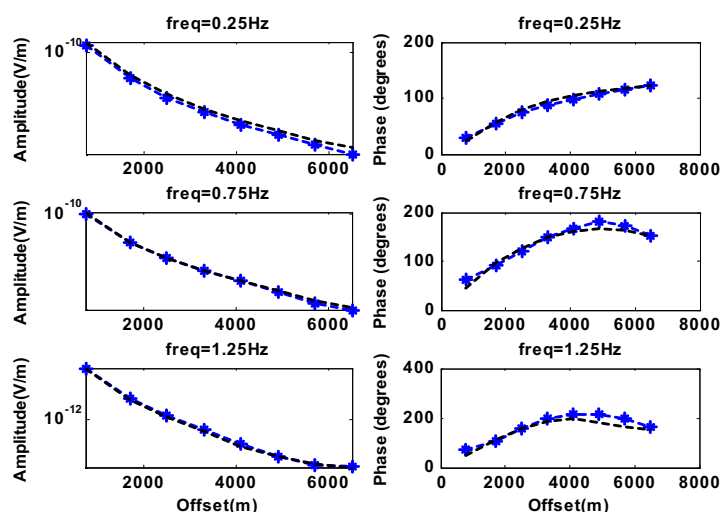


Figure 3. Observed CSEM data at receiver 16 along the EM survey line at Troll field site and calculated data from joint inversion. Blue dashed-star lines represent the field data, black lines represent the calculated data.

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